Depression Analysis using Electroencephalography Signals and Machine Learning Algorithms

Nirmal Varghese Babu
Department of Computer Science and Engineering
Karunya Institute of Technology and Sciences
Coimbatore, India
nirmalvarghese@karunya.edu.in

Dr. E. Grace Mary Kanaga
Department of Computer Science and Engineering
Karunya Institute of Technology and Sciences
Coimbatore, India
grace@karunya.edu

***Abstract*—Depression has been defined as a silent disease that affects everyone regardless of physical or biological state. More than 40% of the population is openly afflicted by the disease. Depression has become a troubling trend, affecting not just a person's psychological well-being but also his or her physical well-being.Electroencephalography (EEG), for example, may identify the effects of depression in the brain. Doctors and researchers can use the tests to analyse the electrical activity of the brain. The electroencephalography signals are used to analyse depression in the proposed work. Data Collection, Data Preprocessing, Feature Extraction, and Classification are the tasks.In the procedure, three main sorts of data are employed. A total of five machine learning algorithms are deployed. Each dataset is compared to the associated algorithms. In all three datasets, the Random Forest method outperformed the other algorithms in terms of accuracy. Furthermore, depression is divided into three categories during the procedure.**

***Index Terms*—Human Brain, Electroencephalography Signals, Depression, Data Pre-Processing, Feature Extraction, Machine Learning**

I. Introduction

A. Human Brain

The brain is one of the human body's biggest and most complicated organs. It is made up of around 100 billion nerves that communicate through trillions of synapses. The brain is a marvellous three-pound organ that directs all body functions, analyses external information, and embodies the essence of the intellect and soul. Many things are controlled by the brain, including intelligence, creativity, emotion, and memory. The cerebrum, cerebellum, and brainstem comprise the brain, which is protected within the skull. The brain receives information from our five senses: sight, smell, touch, taste, and hearing, and it frequently receives information from many senses at the same time. It assembles the messages for us in a meaningful way and can retain the information in our memory. The brain controls our thoughts, memory, and speech, as well as the movement of our arms and legs and the operation of many of our body's organs.

B. Electroencephalography

Electroencephalography, or EEG, is the physiological method of choice for recording the electrical activity generated by the brain using electrodes implanted on the scalp surface. For faster administration, electrodes are affixed to elastic caps similar to swimming caps, guaranteeing that data is acquired from identical scalp sites among all respondents.

The typical clinical EEG bandwidth focuses on waves ranging from 0.5Hz to 70Hz. This research is carried out by applying bandpass filtering on EEG recordings. A broader EEG bandwidth, on the other hand, has been researched and proved to be clinically significant in specific conditions by clinical neurophysiologists and researchers. The elimination of the lower (infra-slow) or higher (ultra-fast) parts of the EEG frequency spectrum in normal EEG results in the loss of many physiological and pathologically relevant brain activity features.

a) EEG Frequency Bands:

- Delta(1 - 4Hz) : Delta waves are measured to determine the depth of sleep. The deeper the sleep, the stronger the delta rhythm. Increased delta power (the number of delta wave recordings) has also been linked to increased focus on internal working memory activities.
- Theta (4 -7 Hz) : Memory encoding and retrieval, as well as cognitive effort, are all related with a wide variety of cognitive processing. When we are faced with challenging tasks (for example, counting backwards from 100 in increments of 7, or recalling the trip home from work), theta waves become more apparent. Theta is also linked to increasing tiredness levels.
- Alpha (7 -12Hz) : When we close our eyes and become peaceful, alpha waves take over. When you are in a calm state of alertness, your alpha levels rise. Alpha waves are frequently used in biofeedback training to monitor relaxation. They're also associated with inhibition and focus.
- Beta (12 -30Hz) : It executes actions of any body part, beta frequencies become stronger across motor areas. Surprisingly, this rise in beta is also visible when we witness other people's physiological motions. Our brain appears to replicate their limb motions, revealing the existence of a complex "mirror neuron system" in our brain that may be governed by beta frequencies.
- Gamma (more than 30Hz) : Gamma represents attentive concentrating and acts as a carrier frequency for data flow across brain areas. Others correlate gamma with quick eye movements, known as micro-saccades, which are thought

to be essential for sensory processing and information intake.

C. Depression

Depression is a very frequent mental illness. It is believed that 5% of individuals worldwide suffer from the illness. It is distinguished by chronic unhappiness and a loss of interest or pleasure in formerly rewarding or pleasurable activities. It can also interfere with sleep and appetite. Tiredness and lack of attention are frequent symptoms. Depression is a primary cause of disability worldwide, contributing significantly to the global illness burden. Depression's consequences can be long-lasting or recurring, and they can have a significant impact on a person's capacity to function and live a fulfilling life. Depression is caused by complex interplay between social, psychological, and biological variables. Childhood hardship, loss, and unemployment all contribute to and may hasten the onset of depression. Depression can be treated both psychologically and pharmacologically. However, therapy and support services for depression are frequently nonexistent or undeveloped in low- and middle-income nations. It is believed that more than 75% of persons in these nations suffering from mental problems do not obtain treatment.

Electroencephalography (EEG), for example, may identify the effects of depression in the brain. Doctors and researchers can use the tests to analyse the electrical activity of the brain. Certain areas of the brain, such as those involved for behaviour, appear to be more active in persons who are sad than in those who are not.

II. Previous Works

This section discusses prior efforts or current systems in the relevant field. From 2016 to 2022, several journals are collected from the relevant journals.

According to Wajid Mumtaz et al. (2019), two deep learning architectures, one dimensional convolutional neural network (1DCNN) and 1DCNN with extended short-term memory (1DCNN-ESTM), were presented (LSTM). Deep learning architectures, such as the one suggested here, automatically discover patterns in EEG data that may be used to distinguish between depressed and healthy controls. Using resting-state EEG data from 33 MDD patients and 30 healthy controls, In [4], a suggested machine learning (ML) approach, was tested and verified. The strength of numerous EEG frequency bands, as well as EEG alpha inter hemisphere asymmetry, were evaluated as input characteristics to the proposed ML system in order to identify MDD patients from healthy controls and prove its usefulness for depression diagnosis. According to [5], DepHNN (Depression Hybrid Neural Network) is a one-of-a-kind EEG-based computer-aided (CAD) Hybrid Neural Network for depression screening. The proposed approach for sequence learning makes use of Convolutional Neural Network (CNN) architectures for temporal learning, windowing, and long-short term memory (LSTM) architectures. According to Hesam Akbari et al.(2021), they suggest a new depression diagnostic index (DDI) based on the FI of IMFs in the VMD domain. This combined score would aid in the faster and more objective detection of normal and depressed EEG signals. The suggested computerised framework and the DDI can both assist health professionals, major organisations, and product developers in the development of a real-time system. In [8], a deep model is built to detect depression using a mix of Convolution Neural Network (CNN) and Long Short Term Memory (LSTM). CNN and LSTM are used to learn the local characteristics and the EEG signal sequence. Table 1 provides a comparative study of existing methodologies and procedures.

According to Abdul Qayyum et al. (2020), there are two separate hybrid deep learning models for categorising and evaluating depressed individuals. Furthermore, by merging a convolutional neural network with Gated recurrent units (RGUs), the proposed network is shallower and substantially less in size than the LSTM network. According to S. Dhananjay Kumar et al. (2019), LSTM (Long-short term memory) deep learning models are used to estimate depression trends for future time instants based on the recovered attributes. The statistical time-domain feature encompassing the data's mean amplitude is extracted from the gathered EEG signals using moving window segmentation. To diagnose depression using EEG data [14], a deep hybrid model was created utilising convolutional neural network (CNN) and long-short term memory (LSTM) architectures. CNN layers are used in the deep model to learn the temporal features of the signals, whereas LSTM layers are used in the sequence learning process. EEG data from the left and right hemispheres of the brain were used in the study. In [15] constructed a one-dimensional Convolutional Neural Network (1-D CNN) to extract more effective features from EEG signals, then integrated gender and age factors into the 1-D CNN via an attention mechanism, which could prompt the 1-D CNN to investigate complex correlations between EEG signals and demographic factors, ultimately generating more effective high-level representations for the detection of depression. In [16] developed a one-of-a-kind method for detecting moderate depression using electroencephalography (EEG). Graph theory was used to explore the functional link network of moderate depression. suggested a unique classification approach for detecting mild depression Given CNN's superior capacity to handle two-dimensional data, we used it to independently apply CNN to the two-dimensional data form of functional connectivity matrices from five EEG bands (delta, theta, alpha, beta, and gamma). In addition, inspired by recent advances in deep recurrent CNNs' ability to detect mental load, the researchers combined the functional connectivity matrices from the three best-performing EEG bands into a three-channel picture to use the CNN to differentiate between moderate depression-related and normal EEG signals.

III. Proposed System

The proposed method analyses depression using electroencephalogram signals and machine learning techniques. Data Acquisition, Data Pre-Processing, Feature Extraction, and

TABLE I
TABLE SHOWING THE EXISTING TECHNIQUES AND METHODS AS A COMPARATIVE ANALYSIS.

Author	**Dataset Used**	**Feature Extraction**	**Algorithm**	**Accuracy (%)**
Wajid Mumtaz et al.(2019)	Hospital Data	-	1DCNN, 1DCNN+LSTM	98.32
Hanshu Cai et al.(2020)	Hospital Data	EEG Linear & Non Linear Features	KNN	73.14
			SVM	66.36
			DT	66.89
Wajid Mumtaz et al.(2017)	Hospital Data	EEG Alpha Interhemispheric Asymmetry, EEG Spectral Power	Logistic Regression	98.33
			Naive Bayes	97.6
			SVM	98.4
Geetanjali Sharma et al.(2021)	Hospital Data	CNN	CNN-LSTM	99.1
Hezam Albaqami et al.(2021)	TUH EEG	Wavelet Transforms	CatBoost	87.68
			XGBoost	86.59
			Light GBM	86.59
Betul Ay et al.(2019)	Hospital Data	-	CNN-LSTM	99.12
Xiaowegi Zhang et al.(2020)	Hospital Data	-	CNN	75.29
Xiaowei Li et al.(2016)	Hospital Data	Power Spectrum Density	SVM	96
Pristy Paul et al.(2020)	Patient Repository for EEG Data	CNN	CNN-LSTM	99.06
S Dhananjay Kumar et al.(2019)	Hospital Data	Time Domain	LSTM	88

Classification are the primary components. Figure 1 shows the proposed system.

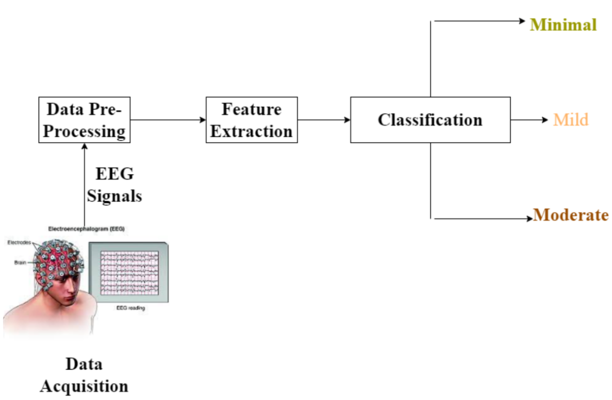


Fig. 1. Proposed System

A. Data Acquisition

The dataset includes resting-state or eyes-closed and eyes-open EEG data from 88 teenagers with minimal (n=30), mild (n=29), and moderate (n=29) depression levels. The current data note comprises raw behavioural (i.e., group, BDI-II score, and PHQ-9 score) and electrophysiological parameters (i.e., absolute and relative EEG powers over 64 electrode sites) data from 30, 27, and 28 participants with minimal, mild, and moderate depression, respectively. These findings will be especially useful in researching the behavioural and electrophysiological signs of adolescents with subclinical depression. It may also be used to compare age groupings and races. The EEG resting state was measured during 30 second sessions with the eyes closed and open. To make continuous EEG recordings, a 10–20 configuration 64-channel Quik-cap electrode set was employed. The ground electrode was placed at AFz, whereas the reference electrodes were placed on the left and right mastoid (M1 and M2). The electrode impedance was kept lower than 5 K.

B. Data Pre-Processing

Preprocessing is the conversion of raw data into a format that is more suitable for subsequent analysis and user interpretation. In the context of EEG data, preprocessing frequently refers to removing noise from the data in order to get closer to the true brain signals. EEG data must be preprocessed for a variety of reasons. To begin with, because spatial information is lost, the signals picked up from the scalp are not necessarily an accurate representation of the impulses coming from the brain. Second, there is a lot of noise in EEG data, which may obscure weaker EEG signals.Blinking and muscle movement, for example, might taint the data and distort the image. Finally, strive to differentiate between significant brain signals and random neural activity recorded during EEG recordings.

The raw EEG waves were processed for data. The preprocessing procedure included offline filtering at 1–40 Hz, baseline correction, and Independent Component Analysis

(ICA) to remove ocular and muscle artefacts. In addition, the EEG recordings were visually inspected to remove any lingering artefacts.

Because EEG is a time-resolving signal, it frequently displays temporal drifts that are unrelated to our experimental topic. Different internal and external causes can cause temporal drifts that vary over time and between electrodes. To limit the impact of such drifts, it is usual practise to do a so-called baseline correction. Essentially, this requires using EEG activity during a baseline period, that is, before an external event, to correct activity during a post-stimulus interval, that is, after an external event. Baseline correction can be accomplished using a variety of methods. The standard procedure is to subtract the mean of a baseline period from each time point in the baseline and post-stimulus periods. Independent Component Analysis (ICA) is a signal processing technique used to differentiate between independent sources that have been linearly mixed in a number of sensors. When recording electroencephalograms (EEG) on the scalp, for example, ICA can filter out artefacts in the data.

C. Feature Extraction

The extraction of features is an important stage in the classification of electroencephalogram (EEG) information. Feature extraction is frequently used as a dimensionality reduction or data compression/reduction approach to help reduce the number of resources required to assess an input signal.

The absolute (uV2) data from segmented and approved EEG epochs were smoothed and averaged over five frequency bands: delta (1–4 Hz), theta (4–8 Hz), lower alpha (8–10 Hz), higher alpha (10–12 Hz), and beta (13–30 Hz). For five frequency bands, absolute and relative EEG powers were calculated.

Absolute (uV2) data were smoothed and averaged across five frequency bands: delta (1–4 Hz), theta (4–8 Hz), lower alpha (8–10 Hz), higher alpha (10–12 Hz), and beta (13–30 Hz). Absolute and relative EEG powers were computed for five frequency ranges.

The Fast Fourier Transform is used to convert a signal from the time domain to the frequency domain (FFT). Any time-dependent signal may essentially be split into a sequence of sinusoids. Long and noisy EEG recordings can therefore be plotted easily in a frequency power-spectrum. This method can uncover hidden traits. No information is lost because the original signal may be reconstructed by summing together all the sinusoids after FFT.

D. Classification

An crucial stage is the categorization of an EEG signal. It is feasible to accomplish this via feature extraction. The feature values are sent into the classifier, which predicts the class of approach. For training data, a huge number of parameters must be taught. In the proposed study, the collected feature data was classified using machine learning methods such as Random Forest, K Nearest Neighbor, Decision Tree, Support Vector Machine, Logistic Regression, and Naive Bayes Algorithm.

TABLE II
PERFORMANCE EVALUATION COMPARISON WITH ACCURACY AND 3 OTHER CRITERIA - WITHOUT HYPER PARAMETER TUNING

Data	Performance Evaluation Comparison						
	Algorithms	RF	KNN	DT	SVM	LG	NB
OSF Dataset 1	Accuracy (%)	85.7	83	50.2	51	51	55.4
	Precision	82	79.9	53.4	48.7	45.7	52
	Recall	87.3	85.3	59.0	54.2	56.9	58.1
	F1 Score	86	81.5	53.4	53	55	57.2
OSF Dataset 2	Accuracy (%)	79.2	72	56.7	60.1	65.6	65.6
	Precision	76.4	69	52.1	57.6	62.9	61
	Recall	82	76.7	60.2	63.2	70.5	68.3
	F1 Score	80	73.1	58.9	61.6	66.4	66.3
OSF Dataset 3	Accuracy (%)	78.9	69	52	51.3	62.3	58
	Precision	73.2	67.8	50.7	48.4	60.1	56
	Recall	82.1	74.9	59	57.5	68.7	60
	F1 Score	79.4	70.6	56	57.5	63.2	58.9

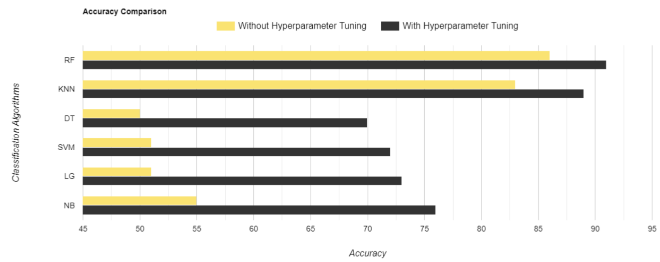
TABLE III
PERFORMANCE EVALUATION COMPARISON WITH ACCURACY AND 3 OTHER CRITERIA - WITH HYPER PARAMETER TUNING

Data	Performance Evaluation Comparison						
	Algorithms	RF	KNN	DT	SVM	LG	NB
OSF Dataset 1	Accuracy (%)	91.4	88.9	70.3	72.3	73.7	76.8
	Precision	86.7	84.5	68	60.1	56.7	68
	Recall	90	87.5	64.6	62	64.5	66
	F1 Score	89.9	85.1	62.8	62	64.8	68.5
OSF Dataset 2	Accuracy (%)	88.7	79	63.3	70.8	78.7	78.7
	Precision	80.4	72.3	59.8	64.5	70.5	69
	Recall	90	86.7	71.2	69.8	78.6	80.1
	F1 Score	88.9	82.3	65.6	70.6	74.3	74
OSF Dataset 3	Accuracy (%)	84.6	72.3	64	61.5	70.8	69.9
	Precision	78.8	77.5	60.7	54.3	75,7	56
	Recall	89.5	84.2	65.4	67.8	77.5	60
	F1 Score	89/1	82.9	61.6	67.8	73.2	67,5

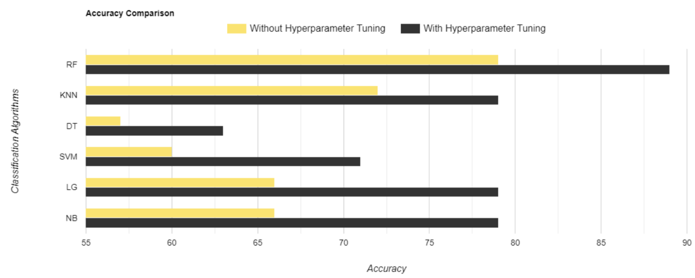
The accuracy score in each situation was recorded. Each method achieves a varied level of accuracy with different types of data, such as Eyes Open, Eyes Close, and the combination of Eyes Close and Eyes Open. During the categorization, depression is divided into three categories: mild, minimal, and moderate, with mild being the lowest and moderate being the most.

IV. EXPERIMENTAL RESULTS

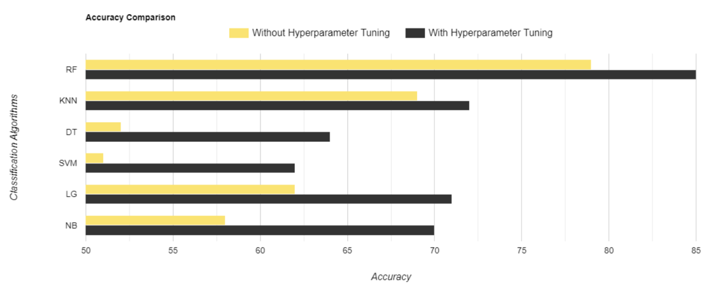
The proposed system functions largely on three separate datasets: Eyes Open Data, Eyes Close Data, and a combination of Eyes Open and Eyes Close Data. Machine learning algorithms employed in the system include Random Forest, K Nearest Neighbor, Decision Tree, Logistic Regression, Support Vector Machine, and Naive Bayes. In terms of accuracy, random forest surpassed other regularly used or existing algorithms. Tables II and III compare performance evaluation based on accuracy and three additional criteria - without and with hyper parameter tuning.



(a) OSF Dataset 1 - Accuracy



(b) OSF Dataset 2 - Accuracy



(c) OSF Dataset 3 - Accuracy

Fig. 2. Graphs showing the accuracy scored by various classification algorithms on OSF Dataset 1,OSF Dataset 2 and OSF Dataset 3 .

Initially, the accuracy of many machine learning algorithms was very low. Later, the parameters of each algorithm were fine-tuned to provide high accuracy or results. Hyperparameters are crucial because they directly regulate the training algorithm's behaviour and have a major impact on the performance of the model being trained. It is the process of improving a model's performance without overfitting or introducing too much volatility. This is accomplished in machine learning by selecting appropriate ”hyperparameters.”

Random Forest scored 89.7 percent, KNN scored 83 percent, Decision Tree scored 50.2, Support Vector Machine scored 51 percent, Logistic Regression scored 51 percent, and Naive Bayes scored 55.4 percent using OSF Dataset 1, while Random Forest scored 79.2 percent, KNN scored 72 percent, Decision Tree scored 56.7 percent, Support Vector Machine scored 60.1 percent, Logistic Regression scored 65.6 percent, and Naive Bayes scored 65.6 percent using OSF Dataset 2. Using OSF Dataset 3, random forest scored 78.9 percent, KNN scored 69 percent, Decision Tree scored 52 percent, Support Vector Machine scored 51.3 percent, Logistic Regression scored 62.3 percent, and Naive Bayes scored 58 percent whereas with the hyper parameter tuning, Random Forest scored 91.4 percent, KNN by 88.9 percent, Decision Tree by 70.3, Support Vector Machine by 72.3 percent, Logistic Regression by 73.7 percent, and Naive Bayes by 76.8 percent using OSF Dataset 1, while Random Forest scored 88.7percent, KNN by 79 percent, Decision Tree by 63.3 percent, Support Vector Machine by 70.8 percent, Logistic Regression by 78.7 percent, and Naive Bayes by 78.7 percent using OSF Dataset 2. Using OSF Dataset 3, random forest scored 84.6 percent, KNN scored 72.3 percent, Decision Tree scored 64 percent, Support Vector Machine scored 61.5 percent, Logistic Regression scored 70.8 percent, and Naive Bayes scored 69.9 percent. Figure 2 shows the graphs showing the accuracy scored by various classification algorithms on OSF Dataset 1,OSF Dataset 2 and OSF Dataset 3 .

V. Summary & Conclusions

Depression is a neurotic or psychotic disorder characterised by sadness, inactivity, difficulty thinking and focusing, a significant increase or decrease in food and sleep length, feelings of dejection and hopelessness, and suicide ideas. Clinicians consider depression to be the most common mental illness.

Women are more prone than men to experience depression. Men's incidence rates climb with age, but women's rates peak between the ages of 35 and 45.

Electroencephalography (EEG) is a non-invasive technique that may be used to assist diagnose mental and neuropsychiatric diseases. The presence of an organic component discovered during the clinical examination is a good predictor of a faulty EEG recording. The non-invasiveness and low cost of the treatment, as well as its ability to evaluate spontaneous brain activity, appear to tempt clinicians to employ it as an investigative tool. However, investigations have found that EEGs obtained through psychiatric referrals had the lowest incidence of abnormality detection. EEG is used in psychiatry to better understand the aetiology and pathogenic processes of mental illnesses, hence improving clinical diagnosis and directing appropriate therapy.It may be useful in clinical circumstances with a possible connection between functional symptoms and organic aetiology. Psychiatrists should employ EEG after doing a comprehensive clinical examination and be aware of the procedure's limitations.

The dataset includes data from both the resting state (eyes open) and the closed state (eyes closed). Following data collection, the data will be pre-processed to remove noise and redundant information. The features will be extracted using the pre-processed data. Signals are classified according to their frequency bands, which include Alpha1, Alpha2, Beta, Theta, and Delta. Classification was done on the obtained features. It was divided into three categories: minimal, mild, and moderate. Machine learning techniques such as Random Forest, K Nearest Neighbor, Decision Tree, Logistic Regression, Support Vector Machine, and Naive Bayes were used in the classification procedure. All of these techniques are implemented in three datasets: OSF Dataset 1, OSF Dataset 2, and OSF Dataset 3. It was observed that Random Forest scored more accuracy when compared to other algorithms in all the 3 datasets.

ACKNOWLEDGEMENT

This work is supported by the Department of Science and Technology - ICPS, Ministry of Science and Technology, Government of India [grant number: DST/ICPS/CLUSTER/Data Science/2018/General]

REFERENCES

[1] Ashima Khosla, Padmavati Khandnor, Trilok Chand, **"Automated diagnosis of depression from EEG signals using traditional and deep learning approaches: A comparative analysis,"** *Biocybernetics and Biomedical Engineering, Volume 42, Issue 1, January–March 2022, Pages 108-142.*

[2] Wajid Mumtaz, Abdul Qayyum, **"A deep learning framework for automatic diagnosis of unipolar depression,"** *International Journal of Medical Informatics, Volume 132, December 2019, 103983.*

[3] Hanshu Cai, Zhidiao Qu, Zhe Li, Yi Zhang, Xiping Hu, Bin Hu, **"Feature-level fusion approaches based on multimodal EEG data for depression recognition ,"** *Information Fusion, Volume 59, July 2020, Pages 127-138.*

[4] Wajid Mumtaz, Likun Xia, Syed Saad Azhar Ali, Mohd Azhar Mohd Yasin, Muhammad Hussain, Aamir Saeed Malik, **"Electroencephalogram (EEG)-based computer-aided technique to diagnose major depressive disorder (MDD),"** *Biomedical Signal Processing and Control, Volume 31, January 2017, Pages 108-115*

[5] Geetanjali Sharma, Abhishek Parashar, Amit M Joshi, **"DepHNN: A novel hybrid neural network for electroencephalogram (EEG)-based screening of depression,"** *Biomedical Signal Processing and Control, Volume 66, April 2021, 102393.*

[6] Mary Judith A, Bagavathi Priya S, Rakesh Kumar Mahendran, **"Artifact Removal from EEG signals using Regenerative Multi-Dimensional Singular Value Decomposition and Independent Component Analysis,"** *Biomedical Signal Processing and Control, Volume 74, April 2022, 103452*

[7] Hesam Akbari, Muhammad Tariq Sadiq, Siuly Siuly, Yan Li, Paul Wen, **"An Automatic Scheme with Diagnostic Index for Identification of Normal and Depression EEG Signals ,"** *International Conference on Health Information Science, HIS 2021: Health Information Science pp 59-70*

[8] Pristy Paul Thoduparambil, Anna Dominic, Surekha Mariam Varghese, **"EEG-based deep learning model for the automatic detection of clinical depression,"** *Physical and Engineering Sciences in Medicine (2020) 43:1349–1360*

[9] Arti Anuragi, Dilip Singh Singh Sisodia, **"Empirical wavelet transform based automated alcoholism detecting using EEG signal features,"** *Biomedical Signal Processing and Control, Volume 57, March 2020, 101777*

[10] Wajid Mumtaz ,Likun Xia ,Mohd Azhar Mohd Yasin ,Syed Saad Azhar Ali ,Aamir Saeed Malik **"A wavelet-based technique to predict treatment outcome for Major Depressive Disorder,"** *Plus One Journal, February 2, 2017, https://doi.org/10.1371/journal.pone.0171409*

[11] Abdul Qayyum, Imran Razzak, Wajid Mumtaz **"Hybrid Deep Shallow Network for Assessment of Depression Using Electroencephalogram Signals,"** *International Conference on Neural Information Processing ICONIP 2020: Neural Information Processing pp 245-257*

[12] S.Dhananjay Kumar, Subha DP , **"Prediction of depression from EEG signal using Long Short Term Memory(LSTM),"** *Proceedings of the Third International Conference on Trends in Electronics and Informatics (ICOEI 2019), IEEE Xplore Part Number: CFP19J32-ART; ISBN: 978-1-5386-9439-8*

[13] Hezam Albaqami, Ghulam Mubashar Hassan, Abdulhamit Subasi, Amitava Datta, **"Automatic detection of abnormal EEG signals using wavelet feature extraction and gradient boosting decision tree,"** *Biomedical Signal Processing and Control Volume 70, September 2021, 102957*

[14] Betul Ay, Ozal Yildirim, Muhammed Talo, Ulas Baran Baloglu, Galip Aydin, Subha D. Puthankattil, U. Rajendra Acharya, **"Automated Depression Detection Using Deep Representation and Sequence Learning with EEG Signals,"** *Journal of Medical Systems (2019) 43: 205 https://doi.org/10.1007/s10916-019-1345-y*

[15] Xiaowei Zhang, Junlei Li, Kechen Hou, Bin Hu, Jian Shen, Jing Pan, Bin Hu, **"EEG-based Depression Detection Using Convolutional Neural Network with Demographic Attention Mechanism ,"** *2020 42nd Annual International Conference of the IEEE Engineering in Medicine amp; Biology Society (EMBC) DOI: 10.1109/EMBC44109.2020, 20-24 July 2020*

[16] Xiaowei Li, Rong La, Ying Wang, Bin Hu, Xuemin Xang, **"A Deep Learning Approach for Mild Depression Recognition Based on Functional Connectivity Using Electroencephalography,"** *Front. Neurosci., 01 April 2020 — https://doi.org/10.3389/fnins.2020.00192*

[17] Ricardo Aler, Inés M. Galván, José M. Valls, **"Applying evolution strategies to preprocessing EEG signals for brain–computer interfaces,"** *Information Sciences, Volume 215, 15 December 2012, Pages 53-66*

[18] Andreas Pedroni, Amirreza Bahreini, Nicolas Langer, **"Automagic: Standardized preprocessing of big EEG data,"** *NeuroImage Volume 200, 15 October 2019, Pages 460-473*

[19] Xiaowei Li, Bin Hu , Shuting Sun, Hanshu Cai, **"EEG-based mild depressive detection using feature selection methods and classifiers,"** *computer methods and programs in biomedicine 136 (2016) 151–161*